An International Comparison of Health Care Expenditure Determinants

Catherine BAC
DREES, Ministère de l'Emploi et de la Solidarité
Yannick LE PEN *
LEN-C3E, Université de Nantes & Euréqua, Université de Paris I

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Abstract

In this paper, we estimate a health care demand function for 18 OECD countries for the period 1972-1995. We consider a demand side approach where health expenditure depend on per capita GDP and the relative price of health care. We use panel data unit root and stationarity tests to characterize our data. Then, we test cointegration between our variables with Kao[16] panel data cointegration tests. As we accept cointegration, we compare different estimators (OLS, FMOLS, DOLS). Results give conflicting evidence for the value of health expenditure income elasticity. The least biaised estimator gives a value that exceeds unity.

JEL classification : C12; C22; C23; I10
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*Corresponding author: Faculté des Sciences Economiques et de Gestion. Chemin de la Censive. B.P. 52231 44322 Nantes Cedex 03. France. E-mail : lepen@sc-eco.univ-nantes.fr. The views expressed herein are those of the authors and not necessarily those of the French department for Work and Pension.

1 Introduction

One major characteristic of developped economies is the growing share of health care expenditure in GDP. By consequence, to control, and as much as possible to limit, the increase of those expenditure has became one major issue of governments. In order to do so, we need to know which are the main determinants of health care expenditure and what is their impact. To put things broadly, health care expenditure are usually explained either by a supply or a demand approach. In the former, health care expenditure depend on technical progress and the behavior of medical practitioners through induced demand. In the latter, which is chosen in our paper, health care expenditure depend on the level of per capita GDP and the relative price of health care.

As concerning the effect of per capita income, one major question of health economics (and applied econometrics) is the value of health care expenditure income elasticity. If this elasticity is greater than unity, health care are a luxury good and their increase is a natural outcome of economic growth. This hypothesis was put forward by Newhouse[15]. On an empirical ground, the estimation of health care expenditure income elasticity is very much controversial. First results were obtained with cross-sectional models. With those models, estimates of the GDP elasticity are usually around unity or slightly less suggesting health care are a necessity(Gerdtham et Jonsson[7]). However, cross-sectional models impose unrealistic homogeneity assumption. Hitiris and Posnett[11] use time series data and find "an income elasticity of health spending at or around unity". However, Hansen and King[10] show that Hitiris and Posnett's time series are non-stationary. In this case, the critical assumptions of stationary data in OLS regression are violated, which casts some doubts on previous empirical results. Hansen and King[10], Blomqvist and Carter[4], Murthy and Okunade[20], Okunade and Karakus[22] use a country-by-country framework to estimate health care determinants. In those papers, it appears that most series do contain a unit root and that cointegration between health care expenditure and their determinants is only accepted for few countries.

Recent advances in econometrics, the aim of which is to put altogether time series and panel data econometrics, give us new methods of test and estimation[1]. Roberts[26] applied a dynamic heterogenous panel data estimator to a panel of OECD countries and reported a long-run per capita GDP elasticity exceeding unity. Gerdtham and Löthgren[8] applied panel data

[1] see Baltagi and Kao[1], Banerjee[2] for a synthesis.

unit root and cointegration tests to estimate the relation between health care expenditure and per capita GDP for a sample of 21 OECD countries for the period 1960-1997. Those unit root and cointegration tests have an asymptotic normal distribution and, more importantly, are more powerfull than tests that use only time-series. Gerdtham and Löthgren[8]'s results are in favor of cointegration but they do not discuss how to estimate of these cointegrating relations.

In our paper, we use a panel of 18 OECD countries for the period 1972-1995. Our first objective is to check the hypothesis of cointegration between health care expenditure, GDP and the relative price of health care. Therefore, we apply Kao[16]'s residual-based cointegration tests. Our results show we can reject the hypothesis of no-cointegration. Our second objective is to compare different methods of estimation of the cointegrating relation. Kao and Chiang[17] show that the asymptotic laws of OLS, fully modified OLS (FMOLS) and dynamic OLS (DOLS) in cointegrated panel data are normal. Their Monte Carlo results show that the DOLS outperforms both the OLS and FMOLS estimators in term of mean biaises. We apply these different estimators and compare their results.

This paper has four sections. In section 2, we present our regressions of health care expenditure determinants and comment our data. In section 3, we proceed to a preliminary analysis. We apply individual and panel data unit root or stationarity tests to each series. We complete this section by a country-by-country cointegration analysis. In section 4, we review the asymptotic properties of panel data cointegration tests and of OLS, FMOLS and DOLS estimators in a cointegrated panel. In section 5, we present our empirical results.

2 The determinants of heath care expenditure

We choose a demand function approach to estimate the determinants of health care expenditure. Therefore, per capita health care expenditure are explained by per capita GDP and the relative price of health care. To include all the other country-specific factors which may influence the level of health care expenditure, country-specific intercepts are introduced. As most studies on this subject, this model is essentially *ad hoc* and the choice of right hand side variables is influenced by the numerous contributions on the possible determinants of health care spending[2].

Newhouse[15] made the hypothesis that an industrial nation's per capita

[2]See Gerdtham and Jonsson[7].

GDP is the main determinant of its health care expenditure. In line with this hypothesis, we firstly consider the following *model 1* where health care expenditure are explained by a country-specific effect and per capita GDP :

$$HCE_{i,t} = \alpha_i + \beta Y_{i,t} + u_{i,t}, t = 1, ..., T, i = 1, ..., N \quad (1)$$

where $HCE_{i,t}$ and $Y_{i,t}$ respectively denotes health care expenditure and GDP per capita in logarithm.

We consider *model 2* where the relative price of health care is added to per capita GDP :

$$HCE_{i,t} = \alpha_i + \beta Y_{i,t} + \gamma P_{i,t} + u_{i,t}, t = 1, ..., T, i = 1, ..., N \quad (2)$$

where $P_{i,t}$ is the relative price of health care expenditure in logarithm, i.e. the ratio of the health price index to the GDP deflator. $P_{i,t}$ is included to separate price and income effects.

We use annual data for a sample of 18 countries on the period 1972-1995. Data are extracted from the 2001 OECD[21] Health Data. They include per capita health care expenditure, per capita GDP and a indicator of the relative price of health care. In order to proceed to an international comparison, data are estimated in GDP purchasing power parity (PPP). In common with most studies on this subject, all of these variables are in natural logarithm.

3 Preliminary analysis

In this section, we proceed to a preliminary analysis of our data set. In a first step, we characterize our series with both individual and panel data unit root and stationarity tests. Then we investigate the cointegrating properties of these series for each country.

3.1 Individual and panel unit root tests

In this first step, we check if there is a unit root for health care expenditure, per capita GDP and the relative price of health care. We apply standard augmented Dickey-Fuller (ADF) test and Im, Pesaran and Smith[12] (IPS) panel data unit root test. Then, we consider Kwiatkovsky, Phillips, Schmidt and Shin[18] stationarity test and its extension to panel data by Hadri[9].

3.1.1 Tests of the null of unit root

A standard approach to test for a unit root for each individual time series is to estimate an (ADF) equation (including here a time trend) :

$$\Delta x_{i,t} = \alpha_i + \delta_i t + \beta_i x_{i,t-1} + \sum_{j=1}^{p_i} \gamma_{i,j} \Delta x_{i,t-j} + \epsilon_{i,t}, t = 1, ..., T, i = 1, ..., N \quad (3)$$

where $\Delta x_{i,t} = x_{i,t} - x_{i,t-1}$ and t indicates time trend. The number of lags p_i included to eliminate the residual serial correlation is chosen according to the $k - max$ criterion.

The null hypothesis $H_0 : \beta_i = 0$ that the series $x_{i,t}$ can be characterized by a difference stationary $I(1)$ process is tested against the alternative hypothesis $H_a : \beta_i < 0$ of trend stationarity. The test statistic is the $t-$statistic of the β_i estimate. As the $t-$statistic of the $\hat{\beta}_i$ doesn't have the usual zero-mean $t-$distribution under the null hypothesis, tables of critical values have been calculated by Monte-Carlo methods.

Im, Pesaran and Smith[12] propose a unit root test which exploit the panel dimension of the data set. This test use the average of the N ADF individual t-statistics for $\hat{\beta}_i$:

$$\bar{t_{NT}} = \frac{1}{N} \sum_{i=1}^{N} t_{i,T}(p_i) \quad (4)$$

where $t_{i,T}(p_i)$ is the ADF t-statistic for country i from each country-specific ADF regression with p_i lags. The IPS evaluates the null hypothesis that all of the series contain unit roots :

$$H_0 : \beta_i = 0, \text{ for all } i$$

against the alternative that some series are stationary :

$$H_a : \beta_i < 0, i = 1, ...N_1, \beta_i = 0, i = N_1 + 1, ..., N.$$

This formulation of the alternative hypothesis allows for β_i and the error structure to differ accross groups and also for some of the individual series to have unit roots under the alternative. If the null hypothesis cannot be rejected, we conclude that the panel data series are difference stationary. IPS convert the t-bar statistic into a Z-bar statistic :

$$Z_{\bar{t}} = \sqrt{N} \frac{(\bar{t}_{NT} - E(\bar{t}_{NT})}{\sqrt{Var(\bar{t}_{NT})}} \quad (5)$$

where

$$E(\bar{t}_{NT}) = (\frac{1}{N})\sum_{i=1}^{N} E(t_{iT}(p_i) \mid \beta_i = 0)$$

and

$$Var(\bar{t}_{NT}) = (\frac{1}{N})\sum_{i=1}^{N} Var(t_{iT}(p_i) \mid \beta_i = 0),$$

assuming the country-specific ADF tests t-statisitcs are independant[3]. IPS expect $Z_{\bar{t}}$ to weakly converge to standard normal distribution under the null hypothesis and diverge under the alternative as both N and T tend to infinity such that $\frac{N}{T} \to k$, where k is a positive constant.

3.1.2 Tests of null of stationarity

Kwiatkovski et *alii*[18] proposed a stationarity test which has a null hypothesis of (trend) stationarity and an alternative of unit root with deterministic trend. Each series is decomposed into the sum of a deterministic trend, a random walk and a stationary error component :

$$x_{i,t} = r_{i,t} + \delta_i t + \epsilon_{i,t} \tag{6}$$

where $r_{i,t}$ is the random walk :

$$r_{i,t} = r_{i,t-1} + u_{i,t} \tag{7}$$

$u_{i,t}$ are $n.i.d.(0, \sigma_u^2)$. $u_{i,t}$ and $\epsilon_{i,t}$ are mutually independent across i. The initial value $r_{i,0}$ is treated as a fixed unknown and play the role of a heterogenous constant. The KPSS test is a one-sided LM-test for the null hypothesis of trend stationarity : $H_0 : \sigma_u^2 = 0$ against the alternative of difference stationarity : $H_a : \sigma_u^2 > 0$.

Let $\hat{\epsilon_{i,t}}$ be the residuals from the OLS regression of $x_{i,t}$ on a constant and a linear deterministic trend. The KPSS statistic for each individual series is :

$$\eta_i = \frac{\frac{1}{T^2}\sum_{t=1}^{T} S_{it}^2}{\hat{\sigma_i^2}} \tag{8}$$

[3]The values of $E(t_{i,T}(p_i))$ and $Var(t_{i,T}(p_i))$ have been calculated by stochastic simulation and are reported in Im, Pesaran and Smith[12].

where $S_{it} = \sum_{j=1}^{t} \hat{\epsilon}_{ij}$ is the partial sum of the residuals and $\hat{\sigma}_i^2$ is a consistent estimator of the long-run variance of the disturbance term $\epsilon_{i,t}$ defined as $\sigma_i^2 = \lim_{T\to\infty} T^{-1}(S_{iT}^2)$ [4].

Hadri[9] defines a panel LM test-statistic $\hat{LM}_\tau$ for stationarity as the average of the individual test-statistics :

$$\hat{LM}_\tau = \frac{1}{N}\sum_{i=1}^{N} \eta_i \tag{9}$$

$$= \frac{1}{N}\sum_{i=1}^{N} \left(\frac{\frac{1}{T^2}\sum_{t=1}^{T} S_{it}^2}{\hat{\sigma}_i^2}\right) \tag{10}$$

Hadri[9] shows that given the defined assumptions on $u_{i,t}$ and $\epsilon_{i,t}$, the test statistic $\hat{LM}_\tau$ is asymptotically normaly distributed under the null hypothesis of stationarity :

$$Z_\tau = \frac{\sqrt{N}(\hat{LM}_\tau - \eta_\tau)}{\zeta_\tau} \Rightarrow N(0,1) \tag{11}$$

where $\eta_\tau = \frac{1}{15}$ and $\zeta_\tau^2 = \frac{11}{6300}$ and "⇒" represents convergence in distribution.

3.1.3 Results

ADF test results are displayed in table 1. They show that for most individual health care expenditure and per capita GDP series, we cannot reject the hypothesis of unit root. In the case of health care expenditure, this hypothesis is only rejected for Australia and Austria. As concerning the relative price of health care, the hypothesis of unit root is rejected in five cases : Australia, Canada, Iceland, Netherland for a 5% significance level and also Denmark and the United-States for a 10% significance level. Results from IPS panel data unit root test show that we cannot reject the null hypothesis of unit root for health care expenditure and per capita GDP. However, we can reject this hypothesis for the relative price of health care. series.

Results for stationarity are displayed in table 2. As with the ADF unit root test, they clearly show that we reject the hypothesis of trend stationarity for health care expenditure and per capita GDP. As concerning the

[4] We use a Bartlett window and the lag truncation parameter l_4 =E$[(4(T/100)^{1/4}]$ to estimate σ_i^2.

relative price of health care, we reject this hypothesis for most countries when the significance level is 5%. For this variable, the hypothesis of stationarity is accepted for Australia, Austria, Canada, Denmark, and Iceland. Therefore, these results confirm the ADF conclusions. When we consider Hadri[9] panel data stationarity test, we reject the hypothesis of trend stationarity for health care expenditure, per capita GDP and the relative price of health care. Notice that, because of the short time span, we do not consider the hypothesis of a time break in the deterministic trend of the series.

3.2 Country-by-country cointegration analysis

In this section, we investigate the cointegrating properties between health care expenditure, per capita GDP and the relative price of health care expenditure for each country.

We apply Johansen[13] [14] maximum likelihood ratio tests to each country. The lag number is set to one because of the short time span. There is no constraint on the intercept, which means there is a constant in the cointegration regression and a time trend in the deterministic part of the series. Results are presented in table 6 and table 7. When we consider only cointegration between health care expenditure and nper capita GDP, the number of cointegrating relation is equal to two or sometimes zero. These results are not compatible with previous on unit root or stationarity tests. Table 7 shows that for most countries we accept the hypothesis of one cointegrating relation between health care expenditure, per capita GDP and the relative price of health care. In the case of Irland and Luxemburg, there is no cointegration relation and with Canada we accept the hypothesis of three cointegrating relations. In this former case, it would mean that health care expenditure, per capita GDP and the relative price of health care are stationary which contradicts previous results.

4 Panel cointegration tests and estimation

4.1 OLS, FMOLS and DOLS in panel data

In this section, we make a short presentation of the properties of OLS, DOLS and FMOLS estimation methods with cointegrated panels. These properties have been established by Kao and Chiang[17], Phillips and Moon[25] and Pedroni[24].

Consider the following fixed-effect panel regression :

$$y_{i,t} = \alpha_i + x_{i,t}^{'}\beta + u_{i,t}, i = 1, ..., N, t = 1, ..., T \tag{12}$$

where $y_{i,t}$ are 1×1, β is an $M\times1$ vector of the slope parameters, α_i are the intercepts, and $u_{i,t}$ are the stationary disturbance terms. We assume that $x_{i,t}$ are $M\times1$ integrated processes of order one for all i, where $x_{i,t} = x_{i,t-1}+\epsilon_{i,t}$. Under these specifications, we have a system of cointegrated regressions, i.e. $y_{i,t}$ is cointegrated with $x_{i,t}$ with the assumptions that $y_{i,t}$, and $x_{i,t}$ are independent across cross-sectional units and $w_{i,t} = (u_{i,t}, \epsilon_{i,t}^{'})^{'}$ is a linear process that satisfies the assumptions in Kao and Chiang[17] . The long-run covariance matrix, Ω, of $w_{i,t}$ can be expressed as :

$$\begin{aligned}\Omega &= \sum_{j=-\infty}^{\infty} E(w_{i,j}w_{i,0}^{'}) \\ &= \Sigma + \Gamma + \Gamma^{'} \\ &= \begin{bmatrix} \Omega_u & \Omega_{u\epsilon} \\ \Omega_{\epsilon u} & \Omega_{\epsilon} \end{bmatrix}\end{aligned}$$

where :

$$\Gamma = \sum_{j=1}^{\infty} E(w_{i,j}w_{i,0}^{'}) = \begin{bmatrix} \Gamma_u & \Gamma_{u\epsilon} \\ \Gamma_{\epsilon u} & \Gamma_{\epsilon} \end{bmatrix} \tag{13}$$

and

$$\Sigma = E(w_{i,0}w_{i,0}^{'}) = \begin{bmatrix} \Sigma_u & \Sigma_{u\epsilon} \\ \Sigma_{\epsilon u} & \Sigma_{\epsilon} \end{bmatrix} \tag{14}$$

are partitioned conformably with $w_{i,t}$. We define the one-sided long-run covariance

$$\begin{aligned}\Delta &= \Sigma + \Gamma \\ &= \sum_{j=0}^{\infty} E(w_{i,j}w_{i,0}^{'})\end{aligned}$$

with

$$\Delta = \begin{bmatrix} \Delta_u & \Delta_{u\epsilon} \\ \Delta_u & \Delta_{\epsilon} \end{bmatrix}$$

Kao and Chiang[17] derive limiting distributions for the OLS, FMOLS and DOLS estimators in a cointegrated regression. The OLS estimator of β is

$$\hat{\beta}_{OLS} = [\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{i,t} - \bar{x_i})(x_{i,t} - \bar{x_i})^{'}]^{-1}[\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{i,t} - \bar{x_i})(y_{i,t} - \bar{y_i})^{'}] \tag{15}$$

where $\bar{x_i} = (\frac{1}{T})\sum_{t=1}^{T} x_{i,t}$ and $\bar{y_i} = (\frac{1}{T})\sum_{t=1}^{T} y_{i,t}$. The FMOLS estimator is constructed by making corrections for endogeneity and serial correlations to the OLS estimator $\hat{\beta}_{OLS}$. Let $\hat{\Omega}_{\epsilon u}$ and $\hat{\Omega}_{\epsilon}$ be consistent estimates of $\Omega_{\epsilon u}$ and Ω_{ϵ}. The endogeneity correction is achieved by modifying the variable $y_{i,t}$ with the transformation

$$\begin{aligned} \hat{y}^{+}_{i,t} &= y_{i,t} - \hat{\Omega}_{u\epsilon}\hat{\Omega}^{-1}_{\epsilon}\epsilon_{i,t} \\ &= \alpha_i + x^{'}_{i,t}\beta + u_{i,t} - \hat{\Omega}_{u\epsilon}\hat{\Omega}^{-1}_{\epsilon}\epsilon_{i,t} \end{aligned}$$

The serial correlation correction term has the form

$$\begin{aligned} \hat{\Delta}^{+}_{\epsilon u} &= (\hat{\Delta}_{\epsilon u}\hat{\Delta}_{\epsilon}) \begin{pmatrix} 1 \\ -\Omega^{-1}_{\epsilon}\hat{\Omega}_{\epsilon u} \end{pmatrix} \\ &= \hat{\Delta}_{\epsilon u} - \hat{\Delta}_{\epsilon}\hat{\Omega}^{-1}_{\epsilon}\hat{\Omega}_{\epsilon u}, \end{aligned}$$

where $\hat{\Delta}_{\epsilon u}$ and $\hat{\Delta}_{\epsilon}$ are kernel estimates of $\Delta_{\epsilon u}$ and Δ_{ϵ}. Therefore the FMOLS estimator is

$$\hat{\beta}_{FM} = [\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{i,t} - \bar{x_i})(x_{i,t} - \bar{x_i})^{'}]^{-1}[\sum_{i=1}^{N}(\sum_{t=1}^{T}(x_{i,t} - \bar{x_i})(\hat{y}^{+}_{i,t} - T\hat{\Delta}^{+}_{\epsilon u})] \quad (16)$$

At last, the DOLS estimator can be obtained by running the following regression :

$$y_{i,t} = \alpha_i + x^{'}_{i,t}\beta + \sum_{j=-q_1}^{q_2} c_{ij}\Delta x_{i,t+j} + v_{i,t}$$

Kao and Chiang[17] show that the asymptotic distributions of estimators using the OLS, FMOLS and DOLS are the following :

$$\sqrt{N}T(\hat{\beta}_{OLS} - \beta) - \sqrt{N}\delta_{NT} \Rightarrow N(0, 6\Omega^{-1}_{\epsilon}\Omega_{u\epsilon}), \quad (17)$$

$$\sqrt{N}T(\hat{\beta}_{FMOLS} - \beta) \Rightarrow N(0, 6\Omega^{-1}_{\epsilon}\Omega_{u\epsilon}), \quad (18)$$

$$\sqrt{N}T(\hat{\beta}_{DOLS} - \beta) \Rightarrow N(0, 6\Omega^{-1}_{\epsilon}\Omega_{u\epsilon}), \quad (19)$$

where

$$\Omega_{u\epsilon} = \Omega_u - \Omega_{u\epsilon}\Omega^{-1}_{\epsilon}\Omega_{\epsilon u},$$

and $\Rightarrow$ represents convergence in distribution. The asymptotic law of the OLS estimator depends on δ_{NT} which has the following expression :

$$\delta_{NT} = [\frac{1}{N}\sum_{i=1}^{N}\frac{1}{T^2}\sum_{t=1}^{T}(x_{i,t} - \bar{x}_{i,t})(x_{i,t} - \bar{x}_{i,t})^{'}]^{-1} \times [\frac{1}{N}\sum_{i=1}^{N}\Omega^{\frac{1}{2}}_{\epsilon}(\int_0^1 \tilde{W}_i(r)dW^{'}_i(r))\Omega^{-\frac{1}{2}}_{\epsilon}\Omega_{\epsilon u} + \Delta_{\epsilon u}],$$

where $W_i(r)$ is a standard Brownian motion, and ,

$$\tilde{W}_i = W_i(r) - \int_0^1 W_i(r)dr.$$

Kao and Chiang[17] show that :

$$\delta_{NT} \rightarrow -3\Omega_\epsilon^{-1}\Omega_{\epsilon u} + 6\Omega_\epsilon^{-1}\Delta_{\epsilon u}$$

where $\rightarrow$ represents convergence in probability. Therefore, the asymptotic distribution of the OLS estimator has a non-zero mean. Kao and Chiang[17] defined the bias-corrected OLS, $\hat{\beta}^+_{OLS}$ as :

$$\hat{\beta}^+_{OLS} = \hat{\beta}_{OLS} - \frac{\hat{\delta}_{NT}}{T}$$

such that

$$\sqrt{N}T(\hat{\beta}^+_{OLS} - \beta) \Rightarrow N(0, 6\Omega_\epsilon^{-1}\Omega_{u\epsilon})$$

where

$$\hat{\delta}_{NT} = -3\hat{\Omega}_\epsilon^{-1}\hat{\Omega}_{\epsilon u} + 6\hat{\Omega}_\epsilon^{-1}\hat{\Delta}_{\epsilon u}.$$

Kao and Chiang[17] study the finite sample properties of the OLS, FMOLS and DOLS estimators in cointegrated regressions. They show that the OLS estimator has a non-negligible bias in finite sample, that the FMOLS estimator does not improve over the OLS in general. At last, the DOLS estimator outperforms the other estimators, particularly in terms of mean-bias.

4.2 Panel cointegration tests

Cointegration tests with panel data are much less known and used than cointegration tests with time series. Here we present the residual-based tests proposed by Kao[16] which test the null of no cointegration against the alternative of cointegration. Kao[16] proposed two types of cointegration tests in panel data, the Dickey-Fuller (DF) and the Dickey-Fuller augmented (ADF) types. The DF type tests is calculated from the estimated residuals of the cointegration regression as :

$$\hat{e}_{i,t} = \gamma\hat{e}_{i,t-1} + v_{i,t} \tag{20}$$

where $\hat{e}_{i,t}$ is the estimated residuals from the estimated regression. The null hypothesis of no cointegration takes the following form : $H_0 : \gamma = 1$. The OLS estimates of γ has the following expression :

$$\hat{\gamma} = \frac{\sum_{i=1}^N \sum_{t=2}^T \hat{e}_{i,t}\hat{e}_{i,t-1}}{\sum_{i=1}^N \sum_{t=2}^T \hat{e}_{i,t}^2} \tag{21}$$

Accordingly, four DF-types tests are constructed as follows :

1. $DF_\gamma = \frac{\sqrt{N}T(\hat{\gamma}-1)+3\sqrt{N}}{\sqrt{10.2}}$,

2. $DF_t = \sqrt{1,25}t_\gamma + \sqrt{1,875}N$,

3. $DF_\gamma^* = \frac{\sqrt{N}T(\hat{\gamma}-1)+(3\sqrt{N}\hat{\sigma}_v^2\hat{\sigma}_{0v}^2}{\sqrt{3+7.2\hat{\sigma}_v^4\hat{\sigma}_{0v}^4}}$,

4. $DF_t^* = \frac{t_\gamma+(\sqrt{6N}\hat{\sigma}_v/2\hat{\sigma}_{0v})}{\sqrt{(\hat{\sigma}_{0v}^2/2\hat{\sigma}_v^2)+(3\hat{\sigma}_v^2/10\hat{\sigma}_{0v}^2)}}$,

where $\hat{\sigma}_v^2 = \Sigma_u - \Sigma_{u\epsilon}\Sigma_\epsilon^{-1}$ and $\hat{\sigma}_{0v}^2 = \Omega_u - \Omega_{u\epsilon}\Omega_\epsilon^{-1}$. While DF_γ and DF_t are based on assuming the strict exogeniety of the regressors with respect to the errors in the equation, DF_γ^* and DF_t^* are for cointegration with endogenous regressors. For the ADF test, we can run the following ADF regression :

$$\hat{e}_{i,t} = \gamma\hat{e}_{i,t-1} + \sum_{j=1}^{p}\vartheta_j\Delta\hat{e}_{i,t-j} + v_{i,tp}. \tag{22}$$

$$ADF = \frac{t_{ADF} + (\sqrt{6N}\hat{\sigma}_v/2\hat{\sigma}_{0v})}{\sqrt{(\hat{\sigma}_{0v}^2) + (3\hat{\sigma}_v^2/10\hat{\sigma}_{0v}^2)}} \tag{23}$$

where t_{ADF} is the t-statistic of γ in the ADF regression. The asymptotic distribution of $DF_\gamma, DF_t, DF_\gamma^*, DF_t^*$, and ADF converge to a standard normal distribution $N(0,1)$.

5 Estimation of health care determinants with a panel data

Estimations and tests are run with the NPT 1.2 program given by Chiang and Kao[5]. Results with Kao[16] panel data cointegration tests for *model 1* and *model 2* are reported in Table 3. For *model 1*, we reject the null hypothesis of no cointegration with all test statistics. For *model 2*, we reject the null hypothesis of no cointegration with all test statistics except DF_t at 5% significance level. Therefore the hypothesis of cointegration among all these variables is strongly supported.

The estimated coefficients are reported in table 4 for *model* 1 and table 5 for *model 2*. *OLS* estimates have the expected sign but the coefficient of the relative price of health care expenditure, $P_{i,t}$, is not significant. However, as shown in previous section, *OLS* estimates are generally biaised due to the endogeneity problem. Therefore, t-statistics do not have a usual t-distribution and we cannot put much confidence on them. The adjusted *OLS* estimated are not much different from *OLS* estimates. The value of

the coefficient of $Y_{i,t}$ is quite the same and the coefficient of $P_{i,t}$ becomes positive but remains insignificant.

The *FMOLS* and *DOLS* estimator[5] correct for the endogeneity bias. The estimated coefficients from these two estimators appear to be very different even if the asymptotic distributions of the *FMOLS* and *DOLS* are the same as shown by Kao[16]. As a matter of fact, with the *FMOLS* estimator, the coefficient of $Y_{i,t}$ is smaller than unity, which imply that health care is not a luxury good, while the estimated coefficient of $Y_{i,t}$ exceeds to unity with the *DOLS* estimator. In both cases, this coefficient is significant. As concerning the effect of $P_{i,t}$, we can observe the same opposition. With the *FMOLS* estimator, the coefficient of $P_{i,t}$ is negative and significant while it remains significant but becomes positive with the *DOLS* estimator. Therefore, these results are in strong contradiction, and their implications for the health care policy are very much different.

From an econometric point of view, however, Kao and Chiang[17] show that the *DOLS* estimator outperform both the *OLS* and *FMOLS* estimators in terms of mean biaises. By Monte-Carlo simulations, they show that the FMOLS leads to a significant biaises and advocate the DOLS estimator. Kao and Chiang[17] notice that the DOLS estimator differs from the FMOLS in that it does not require initial estimation nor nonparametric correction.

6 Conclusion

In this paper we use a panel and time-series framework to test the hypothesis of cointegration between health care expenditure, per capita GDP and the relative price of healt care. However, in a recent paper, Banerjee, Marcellino and Osbat[3] show that a country-by-country analysis is a compulsory initial step when we apply panel data cointegration tests. The number of cointegrating relations at the individual level may biaised the results of the panel data cointegration tests. Kao's[16], Mc Coskey and Kao's[19] and Pedroni's[23] cointegration tests, which are residual-based tests, make the implicit assumption that there is zero or only one cointegration relation for the whole sample of countries. Banerjee, Marcellino and Osbat[3] show if there is for instance more than one cointegrating relation for a country and zero for another, panel cointegration tests may lead us to accept the hypothesis of one cointegrating regression for each country in the sample. Our preliminary country-by-country cointegration analysis show that this condition is not satisfied here. However,we can ask if the Johansen cointegration test can uncover the exact number of cointegration relations.

[5]The *DOLS* estimator was applied with one lead and two lags, that is to say $(q_1, q_2) = (1, 2)$. Results are not much different with $(q_1, q_2) = (1, 1)$ or $(q_1, q_2) = (2, 2)$

A second result of our paper is to apply different methods of estimation of this cointegration relation in panel data. The FMOLS and DOLS estimators lead to strongly different conclusions. With the FMOLS, health expenditure have an income elasticity smaller than one while greater than one with the DOLS. Furthermore, the effect of the relative price of health is negative and significant with FMOLS but positive and significant with DOLS. So the economic implications of these results are quite divergent. We must add that Monte Carlo simulation indicate that the DOLS estimator is the least biaised estimator. Besides, we concentrate herein on the demand side, but future work should include supply side determinants of health expenditure. We should also take account of possible structural break, particularly for the relative price of health care.

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Table 1: *Estimated lag orders, country-by-country ADF t-statistics and IPS standardized panel data unit root tests based on ADF regressions with intercept and time trend for 18 OECD countries 1972-1995.*

Countries	Health expenditure		GDP		Health care price	
	Lag order	ADF test	Lag order	ADF test	Lag order	ADF test
Australia	2	$-5,21^{*}$	0	-1,14	1	$-4,11^{*}$
Austria	4	$-7,43^{*}$	0	-0,55	0	-1,87
Belgium	0	-2,14	0	-1,11	0	-0,99
Canada	2	0,17	0	-1,16	3	$-4,43^{*}$
Denmark	0	-0,88	3	-2,86	1	$-3,47^{**}$
Finland	3	1,33	1	-2,52	4	-0,83
France	0	-0,29	4	-0,35	0	-0,66
Germany	0	-2,02	0	-0,31	0	1,55
Iceland	0	-0,44	0	-0,84	2	$-4,56^{*}$
Ireland	0	-1,87	0	-1,87	0	-2,17
Italy	0	-0,26	0	-0,03	3	-3,06
Luxemburg	0	-1,05	1	-2,79	0	-0,53
Netherland	1	-3,15	0	-1,16	0	$-6,45^{*}$
Norway	0	-1,19	1	-0,98	0	-2,40
Spain	1	-1,89	2	-1,57	0	-2,44
Switzerland	0	-0,81	0	-0,35	0	-2,49
UK	0	-1,12	0	0,09	0	-2,99
USA	1	-0,31	0	0,08	2	-3,57
Panel tests						
$Z_{\bar{t}}$		5,21		2,73		-2,77

Note (a) Lag orders are calculated according to the k-max criterion with a maximum length of 5 periods. (b) For the individual tests, the 5% and the 10% critical values are -3.00 and -3.33 respectively (from Fuller[6]) (c) For the IPS panel test, the 5% and the 10% critical values are -1.645 and -1.282 respectively. (d)* and ** represent 5% and 10% levels of significance.

Table 2: *KPSS test-statistic for individual countries and Hadri[9] standardized panel data test of the trend stationarity test for 18 OECD countries 1972-1995.*

Countries	Health expenditure l_4	GDP l_4	Health care price l_4
Australia	0.2154*	0.2260*	0.0882
Austria	0.1642*	0.2260*	0.1134
Belgium	0.2077*	0.2188*	0.1586*
Canada	0.2249*	0.2272*	0.0754
Denmark	0.2269*	0.2260*	0.0999
Finland	0.2082*	0.2130*	0.1898*
France	0.2268*	0.2229*	0.1620*
Germany	0.2276*	0.2282*	0.1480*
Iceland	0.2229*	0.2255*	0.0397
Ireland	0.1545*	0.1559*	0.1909*
Italy	0.1910*	0.2256*	0.2008*
Luxemburg	0.1899*	0.0855	0.1987*
Netherland	0.1983*	0.2238*	0.1588*
Norway	0.2261*	0.2319*	0.1247**
Spain	0.1184	0.1934*	0.2084*
Switzerland	0.2171*	0.2089*	0.1816*
UK	0.2267*	0.2250*	0.2020*
USA	0.2232*	0.2307*	0.1628*
Panel tests			
Z_τ	16.58*	16.58*	9.8747*

Note : (a) The laglenght of the Bartlett window variance estimator is set to $l_4 = \mathrm{E}[4(T/100)^(1/4)]$. (b) For the individual tests, the 5% and the 10% critical values are 0.146 and 0.119 respectively (from Kwiatkovski et *alii*[18]).) (c) For the panel test, the 5% and the 10% critical values are 1.645 and 1.282 respectively. (d)* and ** represent 5% and 10% levels of significance.

Table 3: *Panel Data Cointegration Tests.*

	DF_ρ	DF_t	DF_ρ^*	DF_t^*	ADF
model 1	$-2,838$	$-1,983$	$-10,118$	$-3,335$	$-4,019$
	$(0,002)$	$(0,023)$	$(0,000)$	$(0,000)$	$(0,000)$
model 2	$-1,938$	$-1,531$	$-7,977$	$-2,802$	$-3,680$
	$(0,026)$	$(0,062)$	$(0,000)$	$(0,002)$	$(0,000)$

Note : (a)Number in parenthesis are the p-values. (b) For the panel test, the 5% and the 10% critical values are -1.645 and -1.282 respectively. (c) For the ADF test, the lag order is set to unity. Results are robust to different lag lenghts.

Table 4: *Estimation Results, model 1.*

	OLS	Adjusted OLS	FMOLS	DOLS (1,2)
$Y_{i,t}$	$1,201$	$1,202$	$0,717$	$1,343$
	$(192,14)$	$(71,01)$	$(40,78)$	$(67,61)$
$\bar{R}^2$	$0,98$	$0,98$	$0,82$	$0,88$

Note : numbers in parenthesis are the t-statistics.

Table 5: *Estimation Results, model 2.*

	OLS	Adjusted OLS	FMOLS	DOLS (1,2)
$Y_{i,t}$	$1,2097$	$1,2103$	$0,9417$	$1,1446$
	$(168,55)$	$(66,27)$	$(49,42)$	$(52,23)$
$P_{i,t}$	$-0,0011$	$0,0011$	$-0,4603$	$0,1458$
	$(-0,06)$	$(0,07)$	$(-30,21)$	$(8,32)$
$\bar{R}^2$	$0,98$	$0,98$	$0,89$	$0,90$

Note: numbers in parenthesis are the t-statistics.

Table 6: *Country-by-Country Cointegration tests. Lag* = 1

	Test Statistic			Critical value at 95%	
	λ_{max}	$Trace$	Null hyp.	λ_{max}	$Trace$
Australia	19.36∗	23.59∗	$r \leq 0$	14.07	15.41
	4.23∗	4.23∗	$r \leq 1$	3.76	3.76
Austria	29.32∗	33.77*	$r \leq 0$	14.07	15.41
	4.45∗	4.45∗	$r \leq 1$	3.76	3.76
Belgium	25.59∗	31.41∗	$r \leq 0$	14.07	15.41
	5.82∗	5.82∗	$r \leq 1$	3.76	3.76
Canada	33.38∗	41.48∗	$r \leq 0$	14.07	15.41
	8.30∗	8.30∗	$r \leq 1$	3.76	3.76
Denmark	21.11∗	27.91∗	$r \leq 0$	14.07	15.41
	6.80∗	6.80∗	$r \leq 1$	3.76	3.76
Finland	36.19∗	38.40∗	$r \leq 0$	14.07	15.41
	2.21	2.21	$r \leq 1$	3.76	3.76
France	31.06∗	38.62∗	$r \leq 0$	14.07	15.41
	7.56∗	7.56∗	$r \leq 1$	3.76	3.76
Germany	16.85∗	25.77∗	$r \leq 0$	14.07	15.41
	8.93∗	8.93∗	$r \leq 1$	3.76	3.76
Iceland	25.78∗	34.39∗	$r \leq 0$	14.07	15.41
	8.61∗	8.61∗	$r \leq 1$	3.76	3.76
Irland	8.23	8.33	$r \leq 0$	14.07	15.41
	0.10	0.10	$r \leq 1$	3.76	3.76
Italy	18.67∗	26.42∗	$r \leq 0$	14.07	15.41
	7.44∗	7.44∗	$r \leq 1$	3.76	3.76
Luxembourg	9.35∗	13.47∗	$r \leq 0$	14.07	15.41
	4.12∗	4.12∗	$r \leq 1$	3.76	3.76
Netherland	16.65∗	22.21∗	$r \leq 0$	14.07	15.41
	5.56∗	5.56∗	$r \leq 1$	3.76	3.76
Norway	22.99∗	33.70∗	$r \leq 0$	14.07	15.41
	10.71∗	10.71∗	$r \leq 1$	3.76	3.76
Spain	19.34∗	22.02∗	$r \leq 0$	14.07	15.41
	2.68	4.14	$r \leq 1$	3.76	3.76
Switzerland	15.20∗	19.75∗	$r \leq 0$	14.07	15.41
	4.54∗	4.54∗	$r \leq 1$	3.76	3.76
United Kingdom	22.59∗	26.54∗	$r \leq 0$	14.07	15.41
	3.95∗	3.95∗	$r \leq 1$	3.76	3.76
USA	29.43∗	34.22∗	$r \leq 0$	14.07	15.41
	4.79∗	4.79∗	$r \leq 1$	3.76	3.76

(a) * denotes significant at 5% level.

Table 7: *Country-by-Country Cointegration tests. Lag* = 1

	Test Statistic			Critical value at 95%	
	λ_{max}	$Trace$	Null hyp.	λ_{max}	$Trace$
Australia	21.21∗	36.85∗	$r \leq 0$	20.97	29.68
	11.21	15.64∗	$r \leq 1$	14.07	15.41
	4.43	4.43	$r \leq 2$	3.76	3.76
Austria	31.06∗	41.11∗	$r \leq 0$	20.97	29.68
	9.64	10.06	$r \leq 1$	14.07	15.41
	0.42	0.42	$r \leq 2$	3.76	3.76
Belgium	26.97∗	33.38∗	$r \leq 0$	20.97	29.68
	6.09	6.41	$r \leq 1$	14.07	15.41
	0.31	0.31	$r \leq 2$	3.76	3.76
Denmark	21.28∗	32.84∗	$r \leq 0$	20.97	29.68
	9.19∗	11.56∗	$r \leq 1$	14.07	15.41
	2.36∗	2.36∗	$r \leq 2$	3.76	3.76
Canada	49.41∗	70.30∗	$r \leq 0$	20.97	29.68
	16.97∗	20.89∗	$r \leq 1$	14.07	15.41
	3.92∗	3.92∗	$r \leq 2$	3.76	3.76
Finland	39.82∗	46.00∗	$r \leq 0$	20.97	29.68
	5.79	6.18	$r \leq 1$	14.07	15.41
	0.39	0.39	$r \leq 2$	3.76	3.76
France	41.90∗	54.13∗	$r \leq 0$	20.97	29.68
	7.75	12.23	$r \leq 1$	14.07	15.41
	4.48	4.48	$r \leq 2$	3.76	3.76
Germany	19.05∗	32.24∗	$r \leq 0$	20.97	29.68
	9.30	13.19	$r \leq 1$	14.07	15.41
	3.90	3.90	$r \leq 2$	3.76	3.76
Iceland	33.78∗	52.28∗	$r \leq 0$	20.97	29.68
	9.66	18.51∗	$r \leq 1$	14.07	15.41
	8.85	8.85	$r \leq 2$	3.76	3.76
Irland	14.65	21.06	$r \leq 0$	20.97	29.68
	6.30	6.41	$r \leq 1$	14.07	15.41
	0.11	0.11	$r \leq 2$	3.76	3.76
Italy	19.94	36.36∗	$r \leq 0$	20.97	29.68
	10.22	16.42∗	$r \leq 1$	14.07	15.41
	6.20	6.20	$r \leq 2$	3.76	3.76
Luxembourg	18.16	23.92	$r \leq 0$	20.97	29.68
	5.75	5.76	$r \leq 1$	14.07	15.41
	0.01	0.01	$r \leq 2$	3.76	3.76
Netherland	40.49∗	56.83∗	$r \leq 0$	20.97	29.68
	10.61	16.35	$r \leq 1$	14.07	15.41
	5.74	5.74	$r \leq 2$	3.76	3.76
Norway	27.83∗	44.86∗	$r \leq 0$	20.97	29.68
	14.26∗	17.02∗	$r \leq 1$	14.07	15.41
	2.76	2.76	$r \leq 2$	3.76	3.76
Spain	21.26∗	30.24∗	$r \leq 0$	20.97	29.68
	4.84	8.98	$r \leq 1$	14.07	15.41
	4.14	4.14	$r \leq 2$	3.76	3.76
Switzerland	30.97∗	43.51∗	$r \leq 0$	20.97	29.68
	7.02	12.54	$r \leq 1$	14.07	15.41
	5.54	5.54	$r \leq 2$	3.76	3.76
United Kingdom	32.59∗	42.39∗	$r \leq 0$	20.97	29.68
	5.52	9.80	$r \leq 1$	14.07	15.41
	4.28	4.28	$r \leq 2$	3.76	3.76
USA	35.61∗	63.00∗	$r \leq 0$	20.97	29.68
	23.70∗	27.38∗	$r \leq 1$	14.07	15.41
	3.69	3.69	$r \leq 2$	3.76	3.76

(a) * denotes significant at 5% level.